THE CONTRIBUTION OF MICROWAVE DATA TO DISTRIBUTED HYDROLOGIC MODELING

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ABSTRACT

Remote sensing data offer spatial information on the state of a large variety of environmental parameters, which determine land surface processes. To model these processes, of which the water cycle plays a central role, the PROMET-family of spatial evapotranspiration models was developed. PROMET was given a structure, with allows to maximize the input of remote sensing data on the field- as well as micro- and mesoscale. The model-family consists of a kernel model (a SVAT based on the Penman-Monteith equation and a plant-physiological model for the influence of environmental parameters on canopy resistance) and a spatial modeller, which provides and organizes raster input data on the field-, micro- and mesoscale. Input data from different remote sensing data sources are presently used (ERS-AMI, LANDSAT, NOAA-AVHRR and METEOSAT) both to gather input-data for the model and to validate model results. Model results on the field scale show good agreement with measurements. Spatial data is set up using remote sensing and conventional data sources for a 800 km² watershed in Upper Bavaria.

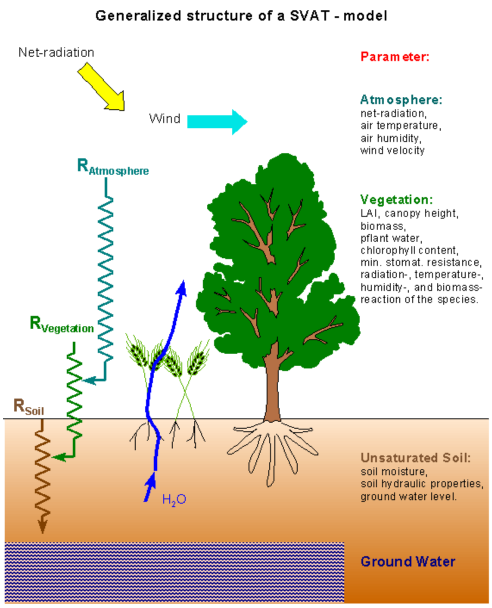

Fig. 1: Generalized SVAT-Scheme

Several examples show the presently possible utilization of remote sensing data and especially microwave data in the model. From these examples a concept for future utilization scenarios for microwave data in hydrologic models is derived.

1. INTRODUCTION

Understanding evapotranspiration (aET) on the land surface is the key to the hydrologic cycle because evapotranspiration rules the partitioning of energy and matter. Evapotranspiration is affected by a multitude of processes at the interface between soil, vegetation and atmosphere. Actual evapotranspiration and the related processes are responsible for app. 70 percent of the lateral global energy transport. Since agricultural production is closely related to evapotranspiration and the water consumption by plants, it also is the key parameter for a secure future food supply. Any change of aET either through a change in vegetation or a change in climate directly affects the available water resources and runoff. Changes in vegetation cover through human influences are taking place both on the field scale through an expansion of agricultural areas and an introduction of new or modified species in agriculture and forestry and on the regional scale through deforestation, irrigation and man-induced erosion. To be able to quantify the effect of these changes on the energy- and water balance of the surface, physically based and distributed models have to be established to describe the distributed nature of the evapotranspiration process on different scales.

A whole wealth of measurements of aET conducted over different land covers and under different climatic conditions at the point scale have demonstrated the large variety and complexity of the evapotranspiration process. Through these measurements energy supply, soil-moisture, temperature and plant development were identified as major limiting factors influencing aET. On the basis of these measurements powerful physically based soil - vegetation - atmosphere - transfer - (SVAT)- models were formulated (see Fig. 1), which describe the processes involved on different levels of complexity for homogeneous surfaces at the point scale [Ref. 1, 2, 3]. The most widely applied of these models was developed by Penman and modified by Monteith [Ref. 4]. It combines the energy balance of the land surface with the concept of a species dependent surface resistance for water-vapour release. Only lately have these SVAT-models been extended from single fields to landscapes [Ref. 5, 6, 7, 8], which became possible through the use of remote sensing data for the determination of slowly changing parameters like land use or topography. Nevertheless this has proven difficult because the models and data structures used were not optimized for the use of remote sensing data. To maximize the utilization of remote sensing data for modeling the hydrologic cycle and to derive sound model-requirements in terms of spatial, spectral and temporal resolution for synergistic remote sensing data from a variety of proposed future missions the model-family PROMET (**Pr**ocess **O**riented **M**ultiscale **E**vapo**t**ranspiration) was developed.

2. MODELING AND INFORMATION FLOW WITHIN PROMET

The information flow within PROMET is shown in Fig. 2. PROMET is based on a flexible data handling shell, which serves three purposes:

organization of input data streams into the system. Spatial data from three different areas can be input to PROMET:
land cover and its change over time (LAI, plant height, albedo)
soil physics and its change over time (soil-moisture)
meteorology (radiation, temperature, wind, humidity).

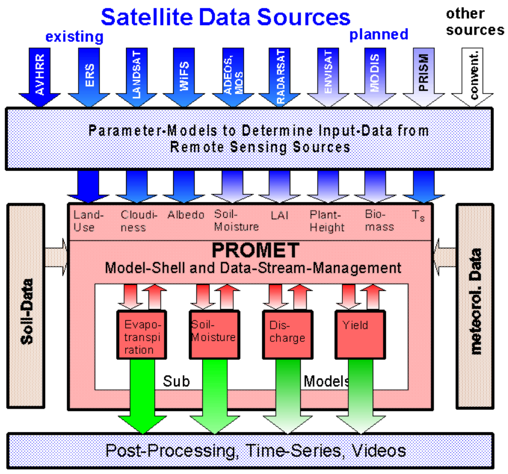

Fig. 2: Information Flow and General Structure of PROMET

Currently derived parameters from METEOSAT, NOAA-AVHRR, LANDSAT and ERS are used in the model.

organization and synchronisation of different submodels, which use the spatial input data streams. Currently sub models for radiation, evapotranspiration, soil moisture and ground water recharge are implemented.
organization of output data streams from the system, productionof time series, digital videos etc.

At the interface between PROMET and remote sensing data sources parameter-models are located, which transform time series of remote sensing observations into meaningful model-parameters.

2.1 ALGORITHM FOR MODELING ACTUAL EVAPOTRANSPIRATION

The kernel model of PROMET uses the Penman-Monteith equation, which regulates evapotranspiration through a canopy resistance, which represents the influence of the environment on plants. This influence is simulated by a coupled plant physiological and a soil hydraulic model. It takes into account plant species, plant growth and soil moisture status through a set of parameters. Each species is represented in the model through the following set of parameters: photosynthetically active radiation (PAR), min. stomatal resistance, increase of stomatal resistance with photosynthetically active radiation, cardinal temperatures consisting of minimum, optimum and maximum air temperature for stomatal resistance, decrease of stomatal resistance with humidity, soil suction, at which stomatal closure starts, slope of the increase of stomatal resistance with soil suction beyond this point.

The influence of plant growth on canopy resistance and energy balance in the model is represented through the temporal evolution of the following parameters: green leaf area index (LAI) , plant height and albedo. These parameters and their change with time, which represents plant growth, should be determined through remote sensing.

Soil water balance, soil suction and moisture in the root zone are determined through a simplified solution of the Richards-equation. The static soil parameters needed to do the calculations are: pore volume, pore size distribution index, bubbling pressure head. The soil-model presently assumes one vertically homogene-ous soil layer, which is represented by the average root depth. A more detailed description of PROMET can be found in [Ref. 7, 19].

3. THE STUDY REGION

To study the spatial distribution of evapotranspiration using remote sensing data within PROMET a typical Central European landscape was chosen. This landscape is characterized through elevation differences, heterogeneous soils and land use, which is mainly man-made in its distribution. The region chosen for this study is the Ammer watershed, which lies in the Northern Alpine Forelands of Upper Bavaria in Germany, a region with undulated to steep terrain, varying soils from clay to sandy loam and high rainfall rates (average >1000 mm/a). The elevation difference between the North and the South of the study region is approximately 1200 m. This and the influence of the Alps introduce a strong N-S gradient in temperature, humidity and rainfall with the tendency of decreasing temperatures and increasing humidity and rainfall towards the Alps.

In Fig. 3 an image of test region as a LANDSAT-TM land use classification overlayed on a digital terrain model is shown [Ref. 9]. Landscape units like cities, forests, lakes and agricultural regions can be seen. As can be seen clearly land use changes with elevation in the test area.

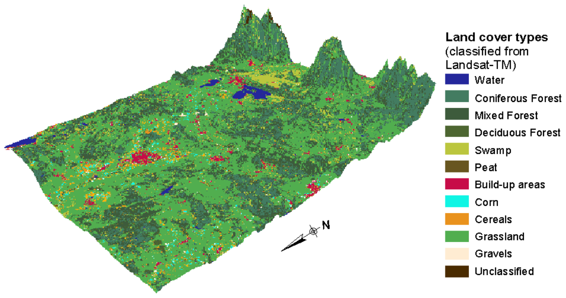

Fig. 3: LANDSAT-TM and ERS based land-use classification of the Ammer watershed

4. REMOTE SENSING INPUTS

Tab. 1 gives an overview of the most important parameters, that enter PROMET together with an estimation of the temporal observation frequency necessary to adequately observe the parameter. The two most time-critical parameters are soil moisture and emergence date, a plant development parameter. For most of the other parameters a weekly to bi-weekly reliable observation is necessary. The right column gives an estimate of the principle capabilities of remote sensing to cover the considered parameter under the assumption that an adequate observing system exists. Presently remote sensing data, which can serve as source for input parameters to PROMET is rare. The reason for this lies in the high demand for multitemporal data and is due to the rapid growth of the vegetation canopy which is described by the parameters LAI (leaf area index), plant height and albedo, as well as the rapid change of soil moisture which for proper observation demand time intervals of 1 day to 1 week respectively. This temporal coverage is very rarely fulfilled with the present high resolution remote sensing systems. No available microwave system can give this coverage. Optical systems with this kind of temporal coverage exist but at the price of degraded spatial resolution. Therefore an attempt is made to demonstrate the current possibilities at the mesoscale using coarse resolution data, before a future scenario to operate PROMET with remote sensing data on a regional scale is presented.

Input and internal model parameters	Required temp. observation frequency	Potential of remote sensing observation
vegetation type	1 year	ü
leaf area index	7 - 14 days	ü
vegetation height	7 - 14 days	ü
biomass	7 - 14 days	ü
fractional vegetation cover	7 - 14 days	ü
surface albedo	7 - 14 days	ü
emergence date	1 - 3 days	ü
root zone depth	7 - 14 days	-
soil moisture	1 - 3 days	ü
soil hydraulic properties	once	-
bare soil roughness	7 - 14 days	ü
topography	once	ü
surface temperature	-	ü

Tab.1: Summary of the spatial parameter requirements of PROMET

Four examples should serve as demonstration of the utilization of present remote sensing data to derive input parameters into the model:

Stolz [Ref.10, included in this publication] shows a strong dependency of the backscatter of grassland on growth height for multitemporal ERS images in the Ammer test area.
Rombach [Ref.11, included in this publication] shows, that surface soil moisture can be derived from ERS-images independent of agricultural cover type for different geographical regions. He also shows, that model results of the soil-moisture content in the Ammer test area using PROMET correspond well with ERS-derived soil moisture distributions.
The next two examples (derivation of temporal albedo changes and large scale soil-moisture index) show, that information on temporal changes of input parameters can even be determined with coarser spatial resolutions.

4.1 Derivation of temporal albedo changes

A time-series of all available cloud-free NOAA-14 AVHRR images of 1995 over Southern Germany was used to determine the temporal development of albedo in the Ammer-watershed. The NOAA-images after geometric correction were calibrated and atmospherically corrected taking into account elevation based on LOWTRAN-7 [Ref.12]. Large enough grassland areas were selected in the Ammer watershed to be able to compare the NOAA-derived temporal course of albedo with the course that has been used within PROMET and which was basically derived from literature. Fig.4 shows the comparison of NOAA-AVHRR-derived albedo, the standard literature values and, as an orientation, the literature and measured values of plant height for the corresponding year. Clearly a similarity can be seen between the changes in the NOAA-albedo and the measured plant height. Albedo tends to increase when plant height of the grassland decreases through cutting (before and after day 190). The measured plant heights as well as the course of albedo do not correspond with the standard literature values because due to a warm Spring in 1995 the onset of vegetation growth was unusually early. What can also be seen clearly is a systematic difference between the absolute value of albedo from literature and derived from NOAA-time series. The literature values are generally too high because literature is usually based on measurements from standard weather stations with short grass. This example clearly shows, that the availability of remote sensing measurements would enable a realistic inclusion of albedo depending on the actual plant development in the model.

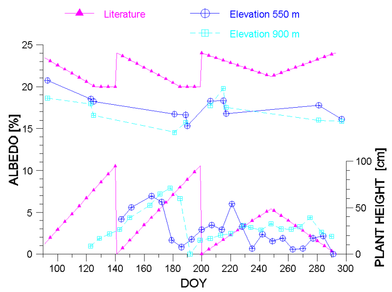

Fig. 4: Comparison between measured albedo (NOAA) and plant height (field) and the literature values presently used in PROMET.

4.2 Derivation of a large scale soil moisture index

An operational data source suitable for mesoscale soil moisture measurement with a spatial resolution compa- rable to AVHRR data is not available yet. Ground mea- surements prove the existence of large spatial differences in soil moisture. The potential of using ERS-SAR-data for soil moisture estimates has been shown previously [Ref. 13, 14, 15, 16]. However, these studies were limited to small test sites and not applicable for mesoscale models. Thus, by spatially degrading ERS data to a resolution of 500 and 1000 m and thereby increasing the radiometric fidelity of the sensor, the applicability of microwave data to determine soil moisture patterns suitable for mesoscale modeling was studied in the Weser watershed in North-Germany (A=40.000 km²).

4.2.1 Methodology

The determination of mesoscale soil moisture patterns is based on the following assumptions: The radar backscatter provided by ERS in agricultural areas depends primarily on soil moisture and surface roughness [Ref. 13], other influencing factors such as row direction average out on mesoscale pixels. Build up areas, forests and lakes do not provide information on soil moisture. Each vegetation type has a typical microwave surface roughness which does not change within the scene [Ref. 17]. Thus given the land use types within a pixel and the specific backscatter for each land use type, the effect of the surface roughness can be corrected by normalizing the signal to a reference crop. Investigating a large number of ERS 1/2 images (13 images) proved, that the backscatter coefficients of wheat and barley do not show significant differences, also sugar beet and potatoes can be treated jointly. Thus only two agricultural landuse types had to be separated within the test site: cereals and root crops. Cereals were selected as reference crop to which the backscatter should be normalized because of their global occurence. The normalisation of the measured backscatter (B) to this reference crop is done according to the following equation:

Eq. 1

$$B_{NORM} = \frac{B_M - B_F*F_F - B_W*F_W - B_B*F_B + F_R*(B_C - B_R)}{(F_R+F_C)}$$

where B stands for backscatter coefficient, F stands for fractional cover of a given land use within a 500-1000 m resolution pixel, subscript $_{NORM}$ stands for normalized to cereal, subscripts $_{F,W,B,R,C}$ stands for forest, water, build up area, root crops and cereals respectively. The

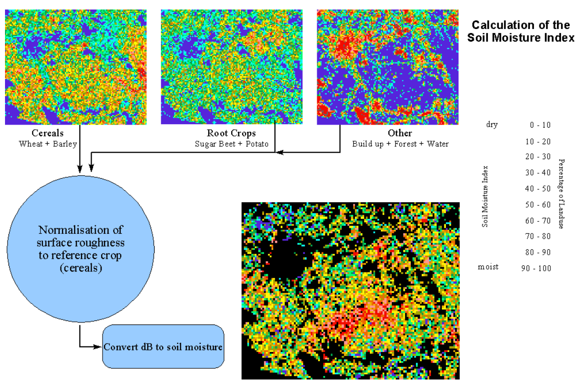

Fig. 5: Schematic scetch for the derivation of the soil-moisture index on spatially degraded ERS-images (spatial resolution: 500 m)

fractional cover of the different land use classes crop was derived by unmixing a NOAA / AVHRR time series of 17 images to determine the fractional cover of the required land-use types. The specific backscatter for each land-use typ was determined from a small section of the ERS image in which the soil moisture was assumed to be constant. The normalized backscatter values were converted to dB and a regression model developed by Rombach [Ref. 18] for barley was used to calculate the soil moisture from the normalised backscatter. Since the results are to some extend dependent upon the surface roughness of the reference crop the calculated moisture may require further adjustments to account for the reference crop surface roughness. However, the resulting image will show spatial differences of the surface soil moisture. Thus the results are given as relative units in the form of a soil moisture index instead of volumetric soil moisture.

Ground truth campaigns conducted in 1996 for three different ERS overflights were used to validate the soil moisture index. Soil moisture was determined over a large number of transsects using TDR-probes. Fig. 6 shows the strong relationship between the calculated soil moisture index and the measured soil moisture. Prior to calculating the soil moisture index, the radar backscatter was normalized to the reference crop as described above. Without the normalization no correlation can be found between calculated soil moisture index and measured soil moisture in Fig. 7.

ERS-images of 1995 were used to create maps of the soil moisture index. Since they are presently hard to validate they were compared with precipitation patterns. An example of the mesoscale soil moisture variability is given in Fig. 5. The black spots in the scene are pixels with a combined coverage of more than 50 % of build up area, forest or water. These pixels were excluded from calculation of the soil moisture index.

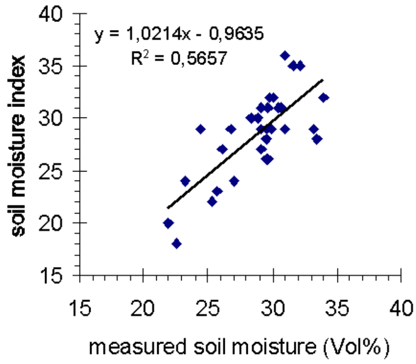

Fig. 6: Comparison of measured soil moisture and calculated soil moisture index with normalization to reference crop

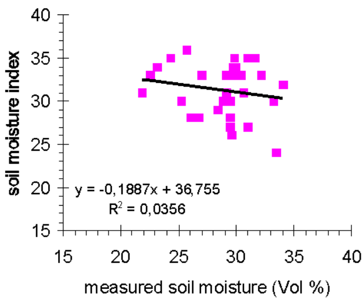

Fig. 7: Comparison of measured soil moisture and calculated soil moisture index without normalization to reference crop

The soil moisture index for July 25, 1995 shows increased moisture in the central part of the test site in yellow and red colors. Three days prior to the overflight no precipitation was recorded in the test area. However, considerable precipitation differences were measured during the most recent precipitation period which started 11 days and ended 6 days prior to the overflight. Hildesheim located closest to the soil moisture peak reported 44.9 mm whereas the measured rainfall in the surrounding area was measured at 12-30 mm. Generally the soil-moisture patterns show good agreement with the measured rainfall patterns. Beyond these first indications and good correlations on the field scale more validation effort is necessary to prove the validity of the observed patterns.

The examples demonstrate, that a broad palette of input parameters to PROMET can be derived both from optical and microwave remote sensing data. In this context microwave data can serve both as input data (plant height, biomass, aerodynamic roughness) and as validation parameter, which can proof, that model calculations are correct (soil moisture). The examples also clearly demonstrate, that the available microwave data from spaceborne sensors can not yet satisfy the data need of realistic, spatially distributed hydrological and land-surface process models. Based on the experience with the data profile, that PROMET requires, strategies were derived for the optimal utilization of remote sensing data in PROMET as well as requirements for future microwave data.

5. SCENARIOS FOR FUTURE MICROWAVE DATA INTEGRATION INTO MODELS

Remote sensing data can be utilized within PROMET in different ways, which are described in the following chapter. Common to all applications is, that remote sensing data has to be converted into a meaningful input or internal parameter through a parameter model, which serves as the interface between remote sensing data and model calculation.

5.1 Determination of model input parameters

The simplest way of using remote sensing data is to provide model input parameters, which are static and do not change with time. These parameters can be obtained by specific parameter models. Examples are land use or topography.

5.2 Update of model input parameters through forcing

If a model input parameter is needed more frequently, because it changes with time, multitemporal remote sensing data should be used to update the parameters through model forcing (Fig.8).

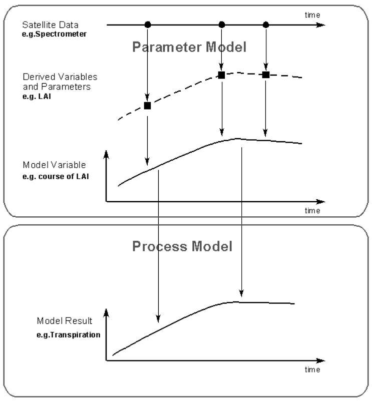

Fig. 8: Updating of model input parameters through model forcing

The remote sensing data sources (in this case optical) deliver data in the form of radiances in irregular time intervals (dots in Fig. 8). A parameter model converts the measurements into model input parameters (rectangles). In a second step the discretely available measurements from remote sensing sources are converted into a continuos stream of values of model parameters through intelligent interpolation (course of LAI in Fig.8). This information can then be used directly in the calculations of the process model, which results in transpiration values.

5.3 Recalibration of internal model parameters

Beyond the use of remotely-sensed observations as surrogate values for one or more conventional parameters in the model, they can also be used to adjust the model during execution. This is illustrated in Fig.9, where the soil-moisture is provided. Soil-moisture is an internal model parameter. It is a required input for the calculation of transpiration and evaporation and at the same time an output of the calculations of the soil water balance. In the example of Fig. 9 a SAR-sensor delivers backscatter values in regular intervals (dots). A parameter model is applied to convert the backscatter values to soil moisture values of the soil surface (rectangles). Soil moisture is non-linearly dependent on precipitation, evapotranspiration, percolation and capillary rise and can therefore not simply be interpolated. The temporal resolutions of existing and planned SAR-sensors are also too coarse for this task. Therefore, soil moisture observations can not be directly used as model input. But one can compare the observations at certain points in time with the soil-moisture, that results from the continuos modeling of the soil water balance (lower part of Fig.8). The difference between modeled and observed soil moisture can then be minimized through recalibration of the SVAT-model. The result is an adjusted course of the soil-moisture, which is externally controlled through measured values.

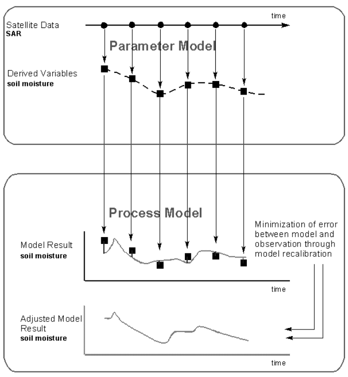

Fig. 9: Recalibration of internal model parameters

5.4 Parameter determination through model inversion

A further step can be conducted, if one not just recalibrates the process model, but inverts it on the basis of the observations to determine land surface parameters. Through parameter optimization using inverse modeling scale dependent effective soil hydraulic functions can be inferred. On the basis of measurements of evapotranspiration and soil moisture in different depth the hydraulic properties of the soils are determined inversely.

A simplified illustration of this type of model inversion is given in Fig. 10. A multi-layer model of the soil water balance is run under the assumption of three different soil types (sand, sandy loam and clay). The model result of surface soil-moisture is then compared to soil-moisture measurements conducted with microwave sensors. The model is inverted by determing the soil-type, for which the temporal patterns of measured and calculated surface-soil-moisture fit best. Weighting functions for the relative importance of the retrieved surface soil-moisture using different SAR-frequencies, which correspond to different penetration depths, must be taken into account for in this approach. In Fig.10 the SAR-measurements show, that the soil in the example is a sandy loam. This is expected to be obtained in the future when multifrequency and multipolarization SAR-data is available.

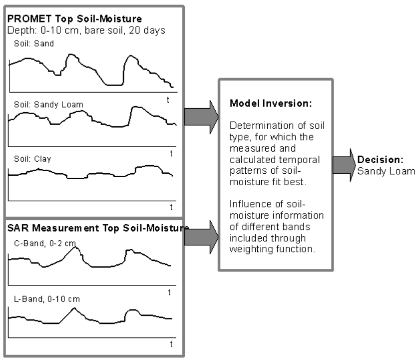

Fig. 10: Soil-physical parameter determination through model inversion

6. CONCLUSIONS

From these four scenarios presented on the utilization of remote sensing data for hydrologic modeling on the land surface and from the large body of evidence on the possibility to extract land surface parameters from remote sensing data through dedicated parameter models the following points seem to be evident:

- to guide remote sensing towards application, data fusion with conventional data and integration of remote sensing derived informatiion into land-surface models is necessary.
- it has been shown that hydrological models (as example for land surface process models) are evolving, which can make extended use of remote sensing data. They should be further developed.
- for land surface application on the regional scale temporal resolution is at least adequately important to spatial and spectral resolution in terms the demand of the evolving hydrologic process models.
- successful use of microwave remote sensing data in hydrologic models can best be achieved through a synergistic and coordinated utilization together with improved optical remote sensing data sources.
- as a first strating point multifrequency / multipolarization coarse resolution microwave sensors are needed, which gather information about the land surface complementary to NOAA-AVHRR.

7. ACKNOWLEDGMENT

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